DOI: https://doi.org/10.15276/hait.08.2025.1
UDC 004.832.2:622.7

Methods of filtering and regression for forecasting noisy timeseries based on machine learning

Olexandr O. Volovetskyi
ORCID: https://orcid.org/0009-0003-1703-387X; ovolovetskyi@gmail.com. Scopus Author ID: 59366887600
Kryvyi Rih National University, 11 Vitaliy Matusevych St. Kryvyi Rih, 50027, Ukraine

ABSTRACT

Predicting parameters in industrial processes is significantly complicated by the presence of noise in sequential measurements, which reduces the effectiveness of technological process control. The aim of the research is to develop an integrated model that combines adaptive noise filtration methods and regression to improve the accuracy of forecasting noisy time series using machine learning algorithms. During the research, a comprehensive database of time series with various levels and types of noise was created, providing a thorough verification of the effectiveness of the proposed methods. The datasets were developed considering the specifics of technological processes and the diversity of noise patterns, which allowed for an accurate evaluation of the developed methods under different conditions. As part of the development of adaptive noise filtration methods, the Kalman filter and wavelet filtration were implemented and optimized. The relationship between the effectiveness of filtration methods and temporal patterns was established: for rapidly changing parameters, wavelet filtration provides higher smoothing efficiency, whereas the Kalman filter better preserves signal characteristics for more stable sequences. To solve the time series forecasting problem, two regression algorithms were implemented and tested – Support Vector Regression and Multilayer Perceptron. It was proven that Support Vector Regression demonstrates better results with low-noise data, while Multilayer Perceptron shows higher stability under significant noise conditions, especially after preliminary filtration. To evaluate the effectiveness of the proposed solutions, a comprehensive quality assessment system was developed that simultaneously considers forecasting efficiency, temporal aspects, noise characteristics, and computational complexity. Experimental confirmation demonstrates that the developed approach improves forecasting accuracy compared to machine learning methods without preliminary filtration, while maintaining acceptable computational complexity. The developed approach is promising for industrial applications, including modeling iron ore enrichment processes, where noise-resistant forecasting is important for process control. The proposed methods can be extended to various industrial processes with similar temporal data and noise characteristics, especially in metallurgical, chemical, and food industries.

Keywords: Kalman filter; wavelet filtration; Support Vector Regression; Multilayer Perceptron; noise-resistant prediction

For citation: **Volovetskyi O. O. "Methods of filtering and regression for forecasting noisy time series based on machine learning".** ***Herald of Advanced Information Technology*** **2025; Vol. 8 No. 1: 13–27. DOI: https://doi.org/10.15276/hait.08.2025.1**

INTRODUCTION

The modern development of industrial technological processes is characterized by increasing demands for control accuracy and final product quality. The problem of forecasting technological parameters under industrial noise conditions becomes particularly relevant, as it directly affects production efficiency and energy consumption. The specifics of continuous production processes create unique challenges for prediction systems due to multiple sources of interference, process nonlinearity, and complex relationships between parameters.

In the context of information technologies, "industrial noise" refers to various types of data distortions occurring in technological process measurements. This includes both physical noise from sensors and equipment (measurement errors, electromagnetic interference, vibrations) and, information noise arising from data transmission processing, and storage systems. The term "data noise" encompasses all these distortions in the digital representation of process parameters, while "information noise" specifically refers to uncertainties and variations in the data that affect the quality of information extraction and decision-making. Understanding these different types of noise and their interactions is crucial for developing effective prediction systems, as they directly impact data quality and, consequently, the accuracy of machine learning models.

With continuous improvement in industrial technologies, there is a growing need to develop adaptive forecasting methods capable of operating effectively at various levels of data noise. Current research demonstrates that traditional approaches to filtering and forecasting do not provide the necessary accuracy in real production conditions. This necessitates the development of an integrated approach that would combine effective filtering methods with adaptive prediction algorithms.

Special attention should be paid to developing an approach for evaluating prediction quality that would consider not only forecast accuracy but also computational efficiency and resistance to various types of interference. Additionally, with the development of Industry 4.0 concepts and implementation of modern information technologies, there is an increasing need to integrate economic and resource aspects into the modeling process, providing deeper understanding of internal mechanisms of prediction systems' operation.

Furthermore, the rapid development of digital technologies and increasing complexity of production processes require implementation of new approaches to noise analysis and algorithm optimization. Systematic investigation of different noise levels' impact allows not only improving model stability but also ensures their applicability across a wide range of industrial tasks. The developed integrated approach demonstrates the potential of using combined filtering and regression methods to achieve high prediction quality, opening new perspectives for automatic control system optimization.

1. ANALYSIS OF LITERARY DATA

Predicting parameters of complex technological processes under noisy data conditions remains a relevant challenge for various industrial systems. Research shows that different types of noise in data can significantly affect the performance of prediction systems. Understanding the impact of various noise types on model accuracy is crucial for developing robust prediction methods. Moreover, proper handling of noise in input data can improve the overall performance of artificial intelligence systems, making prediction models more flexible and accurate [1].

Significant progress has been achieved in developing robust neural networks. Researchers propose using data abstraction methods to reduce noise impact [2]. In the context of industrial systems, special attention is paid to research on technological process optimization, where machine learning-based sensors are developed to predict key quality indicators [3]. For example, in various industrial contexts, such systems can predict quality indicators and impurity content in final products.

The characteristics of complex technological processes create additional challenges for prediction systems. Current research focuses on developing machine learning models for predicting critical parameters such as temperature, pressure, viscosity, chemical composition, and other quality indicators in the final product [4]. An important direction is also product quality prediction, where machine learning algorithms are used to optimize the process and provide recommendations to operators [5].

Unlike previous studies that focused separately on filtration or prediction methods, there is a need for an integrated approach to solving the problem of parameter prediction under noisy conditions. Special attention should be paid to developing a comprehensive indicator for assessing prediction quality that would simultaneously consider forecast accuracy, computational complexity, and resistance to noise of various natures.

Analysis of current research revealed a lack of systematic analysis of normally distributed noise of varying intensity on process parameter prediction quality, insufficient study of comparative effectiveness of different prediction methods under noisy data conditions, and limited research on optimizing computational efficiency of prediction methods considering physical patterns of technological processes.

Thus, there is a need for comprehensive research on noise impact on models' predictive capability and development of methods to increase their robustness while considering computational efficiency, which has determined the direction of this research.

2. RESEARCH GOAL AND OBJECTIVES

The goal of the research is to develop an integrated model that combines adaptive noise filtering methods and regression for improving the accuracy of forecasting noisy time series using machine learning algorithms.

To achieve this goal, the research addresses the following objectives: developing a general structure scheme for the information technology that describes the research process; creating an experimental database of noisy time series for comprehensive validation of the effectiveness of the developed methods; implementing and optimizing adaptive noise filtering algorithms to significantly improve input data quality; deploying regression algorithms to build forecasting models that account for preliminary data processing; conducting a comprehensive analysis of the obtained results to determine the most optimal approaches considering computational efficiency and forecasting accuracy.

3. RESEARCH METHODS

The research was conducted in four stages. In the first stage, basic data sets were formed by generating control points with variable parameter dynamics using USIM PAC software – a specialized tool for modeling and optimizing mineral processing. Simulation was used due to the objective impossibility of obtaining a representative array of real production data with controlled noise levels, which is necessary for comprehensive testing of filtration and regression methods. This software allowed the generation of realistic technological data that accurately reproduce real industrial conditions, avoiding the limitations of real industrial systems: periodicity of technological cycles, complexity of simultaneous parameter recording, and ethical and economic constraints on experiments with active production. Continuous time series were obtained using cubic interpolation, and output parameters were determined by the k-nearest neighbor's method. In the second stage, industrial conditions were simulated by applying normally distributed noise at three intensity levels. The third stage included the development and training of models using adaptive Kalman filtering and wavelet filtering algorithms, as well as training Support Vector Regression (SVR) and Multilayer Perceptron (MLP) models on various data sets. In the final stage, the results were evaluated through analysis of prediction accuracy for different noise levels.

The choice of research methods was justified by their specific properties. Support Vector Regression provided high accuracy in predicting nonlinear dependencies [6], while the MLP demonstrated the ability to detect complex relationships between parameters [7]. The application of adaptive Kalman filtering enabled effective suppression of noise at various intensities [8], while wavelet filtering ensured preservation of important signal features [9].

The experimental part was implemented through the generation of ten datasets for each parameter combination, considering three noise levels and two parameters change rate variants, which ensured statistical reliability of the results.

Generation of Basic Signals. The formation of experimental datasets was implemented in two stages: generation of input parameters and determination of corresponding output values. In the first stage, time series were generated for three input parameters with different statistical properties: Parameter A with normal distribution, Parameter B with uniform distribution, and Parameter C with quasi-constant values with minor fluctuations. Sets ranging from 256 to 8192 points were used to study the effect of sample dimensionality on prediction quality.

The generation of basic signals was carried out by defining control points (5 %, 10 %, or 20 % of the total set size) followed by interpolation. Values for Parameter A were generated according to normal distribution (μ=37, σ=0.33), Parameter B according to uniform distribution (25-35), and Parameter C was maintained close to 100 with minor variations.

For practical interpretation of the results, these abstract parameters can be mapped to real industrial processes. For example, in mineral processing systems, Parameter A might represent material content in raw material (%), Parameter B – percentage of solids in slurry (%), and Parameter C – material flow rate (m³/hr or t/hr).

To obtain continuous time series, cubic interpolation method was applied, described by equation (1):

$$S(x) = a(x-x_1)^3 b(x-x_1)^2 + c(x-x_1) + d, \qquad (1)$$

where coefficients were determined from the conditions of function continuity and its derivatives.

The determination of output parameters (Output X, Output Y, and output rates Z1 and Z2) was implemented using the k-nearest neighbors' method (k=1) with the ball tree algorithm.

The Euclidean distance between the input parameter vector x and point x_i was calculated using formula (2):

$$d(x, x_1) = \sqrt{\sum (x - x_i)^2}. \qquad (2)$$

The ball tree algorithm optimized the search for nearest neighbors by partitioning space into nested hyperspheres [10]. Output parameters were maintained within predefined ranges typical for the studied type of processes.

In the context of material enrichment processes, these output parameters would correspond to content percentage in concentrate (Output X), content percentage in tailings (Output Y), and mass flows of concentrate (Z1) and tailings (Z2).

Modeling of Noise Effects To reproduce real operating conditions of industrial systems, normally distributed noise was introduced into the experimental data as the most characteristic type of interference in industrial measurement systems. The noise level was formed proportionally to the current parameter value, which corresponds to the nature of errors in industrial measuring instruments.

The noise component was calculated using formula (3):

$$noise = N(0, \sigma) sv, \qquad (3)$$

where N(0, σ) is a normally distributed random variable with zero mean and standard deviation σ, sv represents the signal value, and σ is determined as the relative error coefficient (error_percent/100).

Three characteristic noise ranges were defined:

– minimum (min), optimal operating conditions;

– average (aver), typical production conditions;

– maximum (max), complicated operating conditions.

The noise levels for each parameter are shown in Table 1.

Table 1. **Noise levels for parameters (percent of signal value)**

Parameter	min	aver	max
Parameter A	0.5	0.75	1.0
Parameter B	1.0	1.5	2.0
Parameter C	1.0	2.5	4.0
Output X	0.3	0.5	0.7
Output Y	0.4	0.65	0.9
Z1 Flow	2.0	3.5	5.0
Z2 Flow	2.5	4.0	5.5

Source: **compiled by the author**

The experimental base was formed considering six sample sizes (256-8192 points) and three variants of control point density (5 %, 10 %, 20 %). For each of the 18 combinations, three noise variants were created, totaling 54 data groups. Taking into account nine repetitions for each group, the total number of experiments reached 486, ensuring statistical reliability of the results.

Architecture of Predictive Models For time series forecasting in industrial systems, the selection of Support Vector Regression (SVR) and Multilayer Perceptron (MLP) as predictive models was driven by several fundamental considerations related to the nature of industrial processes. Industrial data typically exhibits complex nonlinear relationships between variables along with significant noise components that cannot be adequately modeled using classical linear forecasting approaches. As demonstrated in previous research [11], traditional linear methods often fail to capture the intricate dynamics of complex industrial processes, particularly under varying operational conditions and in the presence of measurement noise.

Support Vector Regression was selected due to its robust mathematical foundation that enables effective generalization with limited training data. The method employs a ε-insensitive loss function that disregards errors falling within a specified threshold, making it particularly suitable for noise-contaminated industrial measurements. This characteristic allows SVR to focus on the underlying patterns rather than attempting to fit noise fluctuations, resulting in models with enhanced generalization capability. Additionally, SVR's kernel-based approach permits the implicit mapping of input data into higher-dimensional spaces without increasing computational complexity, enabling the capture of complex nonlinear relationships present in industrial time series.

The MLP architecture complements SVR by offering different pattern recognition capabilities. The multilayered structure with nonlinear activation functions enables the network to approximate complex functional relationships between inputs and outputs as noted in [12]. For the specific requirements of this research, a carefully designed MLP architecture was implemented with appropriate hidden layers to balance between model complexity and generalization ability. The output layer employs a linear activation function suitable for regression tasks, while the hidden layers utilize nonlinear activation functions to capture the complex relationships in the data. This design choice reflects the specific need to model the continuous nature of the target variables while accounting for the inherent nonlinearities in the process.

The complementary nature of these two approaches provides significant advantages in industrial forecasting applications [13]. While SVR excels at handling outliers and establishing stable decision boundaries, MLP demonstrates superior ability in detecting hierarchical patterns and adapting to evolving process dynamics. By implementing both methods and comparing their performance under various noise conditions, the research provides a comprehensive assessment of predictive capabilities applicable to industrial environments with measurement uncertainty.

To ensure optimal performance of both models, hyperparameter optimization was conducted using RandomizedSearchCV with cross-validation as described in [14]. This approach enabled efficient exploration of the parameter space without exhaustive grid search, balancing computational efficiency with model performance. For SVR, parameters including kernel type, regularization parameter C, and epsilon value were systematically optimized. Similarly, for MLP, the optimization process determined the optimal number of hidden layers, neurons per layer, activation functions, and regularization parameters. This rigorous optimization procedure ensured that both models performed optimally under various experimental conditions and input data noise levels, providing reliable comparison results.

ISSN 2663-0176 (Print)
ISSN 2663-7731 (Online)

Support Vector Regression is based on the principle of structural risk minimization [15], providing optimal balance between model complexity and generalization ability.

For a training dataset $\{(x_1,y_1), ..., (x_n,y_n)\}$, SVR seeks a function described by equation (4):

$$f(x) = \acute{a}w, x\tilde{n} + b, \tag{4}$$

where w is the weight coefficient vector, b is the bias.

The optimization problem is formulated according to equations (5):

$$\begin{gathered} minimize\{0.5\|w\|^2 + C\sum(e_i + e_i^*)\}, \\ s.t.\left|f(x) - y\right| \le e + \xi, \\ \xi_i,\ \xi_i^* \ge 0, \end{gathered} \tag{5}$$

where ξ_i, ξ_i^* are slack variables, ε is the permissible error [16].

For solving nonlinear problems, a radial basis function (RBF) kernel [17] is applied, defined by formula (6):

$$K(x, x') = exp\left(-\gamma\left\|x - x'\right\|^2\right), \tag{6}$$

where $\gamma > 0$ is the kernel parameter. The RBF kernel enables effective modeling of nonlinear dependencies while maintaining computational efficiency [17] and demonstrates high resistance to noise in industrial measurements [18].

Multilayer Perceptron effectively models complex nonlinear dependencies in time series [7]. The MLP architecture includes an input layer, hidden layers, and an output layer with full neuron connections between layers [12].

Each neuron implements nonlinear transformation according to equation (7):

$$y = \varphi\left(\sum w_i x_i + b\right), \tag{7}$$

where φ is the activation function, w_i are weight coefficients, x_i are input signals, b is bias. ReLU activation is used in hidden layers, described by formula (8) [7]:

$$\varphi(x) = \max(0, x). \tag{8}$$

Network training occurs by minimizing mean squared error according to formula (9):

$$E = 1/n\sum\left(y_i - \hat{y}_i\right)^2, \tag{9}$$

where y_i are actual values, $\hat{y}_i$ are predicted values, n is the training sample size [19].

To prevent overfitting, dropout and L2-regularization are applied [20], which is particularly important when working with noisy industrial data. MLP also supports continued training on new data.

Comparative Analysis of SVR and MLP methods reveals their complementary characteristics for industrial time series forecasting [21]. SVR demonstrates higher efficiency on small datasets and noise resistance [22], while MLP provides better adaptability and flexibility in modeling complex dependencies [23]. The main characteristics of the methods can be summarized as follows.

Regarding data requirements, Support Vector Regression demonstrates high effectiveness on small to medium datasets while maintaining sensitivity to data scaling [24], whereas Multilayer Perceptron typically requires larger volumes of data to achieve comparable accuracy but exhibits less sensitivity to scaling issues [25].

From a computational complexity perspective, SVR training operations scale according to $O(n^2)$ [26], making it potentially more resource-intensive for large datasets, while MLP generally follows linear complexity $O(n)$, though the actual computational load varies significantly depending on the selected network architecture and training parameters [27].

In terms of data preprocessing requirements, SVR method necessitates thorough normalization procedures and careful cleaning of outliers to maintain prediction quality, in contrast to MLP which demonstrates greater robustness to various data formats, though it still benefits from standardization of input features for optimal performance.

These fundamental differences inform the selection of appropriate method based on specific application conditions and available computational resources. It has been experimentally confirmed that SVR is more effective for medium-term horizons with noisy data [24], while MLP is better for long-term forecasting and complex pattern detection [25].

Kalman Filtering The choice of adaptive Kalman filtering is justified by several advantages for industrial data processing.

1. Optimality and Recursiveness: The Kalman filter is optimal for linear systems with Gaussian noise, minimizing the mean square estimation error. The recursive nature of the algorithm enables efficient real-time data processing without the need to store the entire measurement history.

2. Adaptability: The ability to automatically adjust filter parameters according to changing noise characteristics makes this method particularly

valuable for industrial systems where conditions may vary.

3. Predictive Capability: The filter not only smooths noisy data but also predicts subsequent values, which is critical for industrial control systems.

To reduce noise effects, adaptive Kalman filtering [28] based on a recursive estimation algorithm is applied.

The process is described by prediction equations (10-11) and correction equations (12-14):

$$\hat{x}_i^- = \hat{x}, \tag{10}$$

$$P_k^- = P_{k-1} + Q, \tag{11}$$

$$K_k = P_k^- / (P_k^- + R), \tag{12}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k + \hat{x}_k^-), \tag{13}$$

$$P_k = (1 - K_k)P_k^-, \tag{14}$$

where $\hat{x}_k^-$ is prediction state, P_k^- is prediction error, Q is process noise variance, K_k is Kalman coefficient, z_k is measurement, R is measurement noise variance [29].

Filter parameters are determined adaptively [30].

The measurement noise variance is estimated using formula (15):

$$\sigma_m = std(\Delta z) / \sqrt{2}, \tag{15}$$

where σ_m is the standard deviation of measurement noise.

The process noise variance is set proportionally to the estimated measurement noise variance according to formula (16):

$$Q = R / 100. \tag{16}$$

This adaptive approach provides an optimal balance between filter sensitivity and its noise suppression capability [31].

Wavelet Filtering was chosen as a complementary method to Kalman filtering for the following reasons.

1. Multi-level Signal Representation: Wavelet transform provides efficient signal analysis at different scales, allowing detection and preservation of significant features even in the presence of substantial noise.

2. Time and Frequency Domain Localization: Unlike Fourier transform, wavelet analysis provides simultaneous localization in time and frequency, which is critical for preserving characteristic signal features such as jumps and sharp changes commonly observed in industrial processes.

3. Data Non-stationarity: The wavelet method is particularly effective for processing non-stationary signals characteristic of industrial processes with transitional modes, stops, and equipment starts.

Discrete wavelet transforms with Daubechies db4 wavelet [32] is used.

The filtering threshold is determined by formula (17):

$$\lambda = \sigma\sqrt{2\ln(N)}. \tag{17}$$

where σ is the noise level estimate, N is the signal length [33].

The coefficients are modified according to rule (18):

$$\begin{gathered} w_i' = sign(w_i)(|w_i| - \lambda),\ |w_i| > \lambda, \\ w_i' = 0,\ |w_i| \le \lambda. \end{gathered} \tag{18}$$

Filtering efficiency is evaluated using formula (19):

$$OFS = w_s SE + w_n NR + w_f FP, \tag{19}$$

where *SE* is smoothing efficiency, *NR* is noise reduction, *FP* is feature preservation, w_s is smoothing weight coefficient, w_n is noise suppression weight coefficient, w_f is feature preservation weight coefficient.

Criteria for Assessing Forecasting Quality A multi-factor approach has been applied to evaluate the effectiveness of forecasting methods. The evaluation is conducted separately for each output parameter: Output X, Output Y, Z1 Flow, and Z2 Flow.

Main evaluation metrics:

1. Root Mean Square Error is determined according to formula (20):

$$RMSE = \sqrt{\sum(y_i - \hat{y}_i)^2/n}. \tag{20}$$

2. Coefficient of Determination is calculated based on formula (21):

$$R^2 = 1 - \sum(y_i - \hat{y}_i)^2 / \sum(y_i - \bar{y})^2. \tag{21}$$

3. Average Coefficient of Variation is established in accordance with formula (22):

$$CV = \frac{\sum(\sigma_i / \mu_i)}{n} \times 100\%. \tag{22}$$

4. Data processing time (processing_time).

Experimental factors include:

– data noise level;

– training sample size (256-8192 points);

– number of support points (5-20 % of dataset size);

ISSN 2663-0176 (Print)
ISSN 2663-7731 (Online)

– forecasting method (SVR, MLP).

Noise resistance assessment [34] is determined through the relative change in metrics, defined by formula (23):

$$\Delta RMSE = \frac{(RMSE_{\max} - RMSE_{\min})}{RMSE_{\min}} \times 100\%, \quad (23)$$

where $RMSE_{max}$ and $RMSE_{min}$ are error values at maximum and minimum noise levels.

Statistical processing of results [35] includes:

– using interquartile range (IQR) for outlier detection;

– calculation of basic statistics (mean, minimum, maximum, standard deviation);

– assessment of statistical significance at α=0.05.

4. EXPERIMENT RESULTS

As a result of the conducted research, a general structure of information technology for predicting noisy time series was developed, as shown in Fig. 1. The developed structure reflects the key stages of data processing and construction of predictive models. The process begins with the generation of control points and cubic interpolation to form basic data sets. Next, noise effects are modeled to create realistic noisy signals, after which parallel filtering methods–Kalman filter and wavelet filtering–are applied. The filtering results are evaluated by calculating the optimal signal function (OSF), which allows obtaining a cleaned signal for further training of machine learning models (SVR and MLP). The final stages of the technology are the evaluation of results and determination of the boundaries for applying the developed methods.

As a result of experimental research, noise characteristics were obtained for seven key parameters of the studied industrial process: three input parameters (Parameter A, Parameter B, Parameter C) and four output parameters (Output X, Output Y, Z1 Flow, Z2 Flow).

Quality indicator parameters demonstrated the highest resistance to noise effects. For Output X, SNR values ranged from 50.46 to 43.08 dB with correlations between clean and noisy signals of 0.93-0.75. The Parameter A is characterized by SNR of 46.01-39.99 dB and correlation of 0.91-0.77, while Parameter B showed SNR of 39.99-34.00 dB with correlation of 0.99-0.96.

Flow rate parameters proved to be more sensitive to noise effects. For Z2 Flow, SNR values were 32.02-25.19 dB with correlation of 0.58-0.32, for Z1 Flow – SNR of 34.01-26.03 dB with correlation of 0.28-0.57.

Detailed analysis of the Output X parameter at maximum noise level showed: *RMSE*=0.3464, *SNR*=43.9 dB, correlation coefficient = 0.7345, standard deviation = 0.3458, outlier percentage = 0.8%. For all studied parameters, the relative deviation of mean values did not exceed ±0.0188, and the percentage of outliers varied from 24.53 % to 31.87 %.

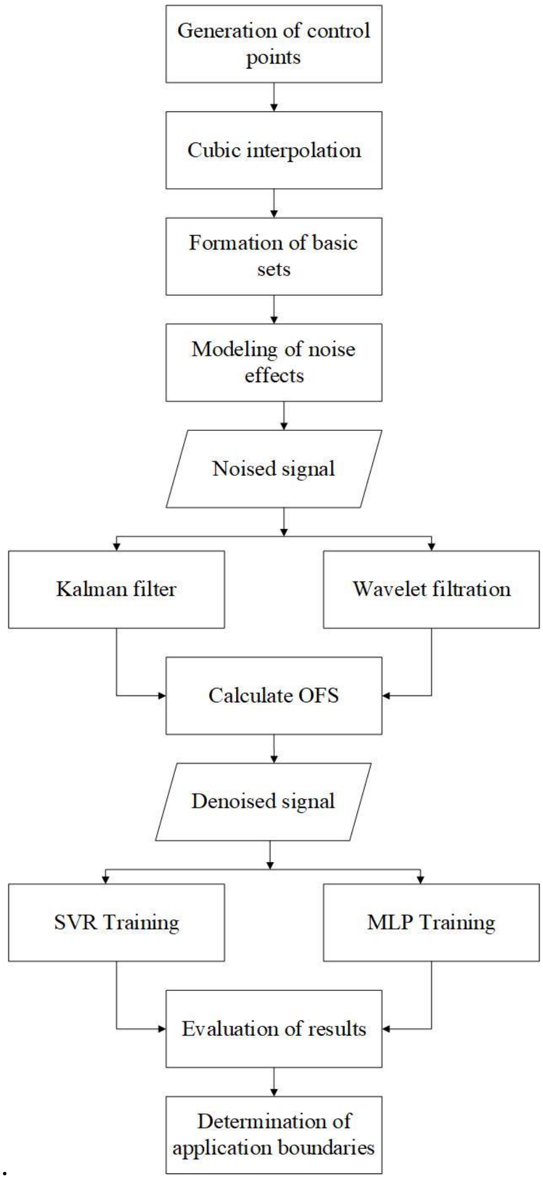

Fig. 1. **General structure of the information technology**
Source: **compiled by the author**

Comprehensive visualization of analysis results for the Output X parameter at maximum noise level is presented in Fig. 2, which includes comparison of clean and noisy signals, noise distribution histogram, signal power spectrum, and correlation relationship between signals.

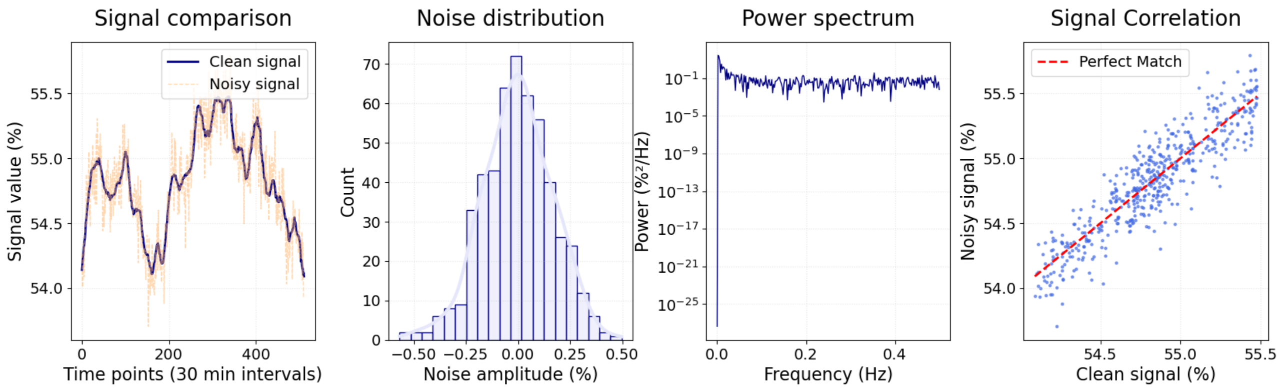

Fig. 2. **Comprehensive analysis of time series quality for prediction system development: a – comparison of original and noise-affected signals; b – noise distribution characteristics; c – frequency domain analysis; d – signal correlation assessment**

Source: **compiled by the author**

Comparative Analysis of Filtering Methods The experimental comparison of Kalman and wavelet filtering methods demonstrated distinct performance characteristics when applied to process parameters in the industrial time series system. The analysis was performed on Output X measurements with moderate noise levels.

The temporal analysis (Fig. 3a) shows the filtering results for a signal with amplitude variations between approximately 52.5 and 54.25 units. It compares the clean signal (solid black line), the noisy signal (dotted gray line), and the results of wavelet filtering (dashed green line) and Kalman filtering (dashed red line). Both filtering methods effectively reduced noise while tracking the underlying signal trends. The wavelet filtering demonstrated slightly better adherence to the clean signal pattern, particularly during rapid transitions, while the Kalman filter showed minor lag in tracking sharp changes.

The spectral analysis (Fig. 3b) illustrates the noise suppression capabilities of both methods. The power spectrum, plotted on a logarithmic scale, reveals that both filters effectively attenuate high-frequency noise components while preserving the fundamental signal frequencies. The noisy signal spectrum (dotted gray line) shows consistently higher power across all frequencies compared to the filtered results and the clean signal (solid black line).

Quantitative performance metrics (Fig. 3c) are presented as a bar chart, comparing wavelet and Kalman filtering across three categories: Smoothing, Noise Reduction, and Feature Preservation. While precise numerical values are not directly displayed on the chart, it's visually evident that wavelet filtering outperforms Kalman filtering in all three categories. The bars for Wavelet filtering are consistently higher than those for Kalman filtering. Recommended method: wavelet

System Parameter Prediction in the Presence of Noise The study of noise influence on the predictability of system parameters was conducted using Support Vector Regression and Multilayer Perceptron.

The comprehensive analysis of prediction methods' effectiveness covered three key aspects:

– temporal efficiency of methods with different training sample sizes;

– impact of control points quantity on prediction quality;

– methods' resistance to various noise levels.

Analysis of prediction methods' time efficiency Fig. 4 shows a comparative analysis of the computational efficiency of SVR and MLP methods with different training sample sizes, including 95% confidence intervals (CI). The figure reveals a significant advantage of SVR in average processing time (85.044 s versus 160.186 s for MLP). At minimum sample size, SVR demonstrates significantly better performance (0.465 s) compared to MLP (15.305 s), although at maximum load, the methods show comparable results (425.628 s and 436.920 s respectively).

The processing time dependency on training sample size shows strong correlation for both methods, with MLP demonstrating practically linear dependence (correlation coefficient 0.995) compared to slightly weaker for SVR (0.943). The relative processing speed of SVR is 0.53 of MLP time, confirming its higher computational efficiency.

ISSN 2663-0176 (Print)
ISSN 2663-7731 (Online)

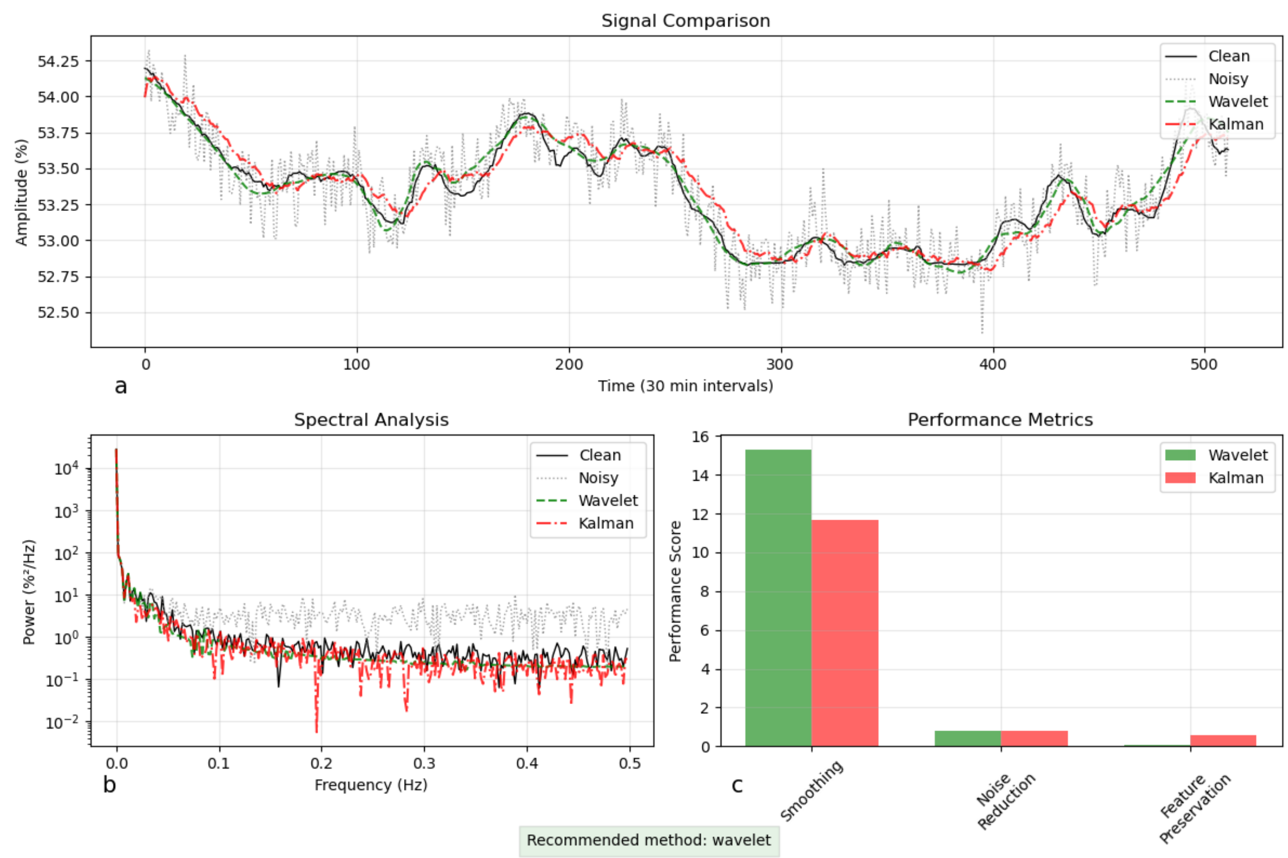

Fig. 3. **Comparison of wavelet and Kalman filtering methods:**
a – time-domain signal comparison showing clean, noisy, wavelet-filtered, and Kalman-filtered signals; b – spectral analysis showing power spectra of clean, noisy, wavelet-filtered, and Kalman-filtered signals; c – comparison of OFS components (SE, NR, FP) between wavelet and Kalman filtering
***Source:* compiled by the author**

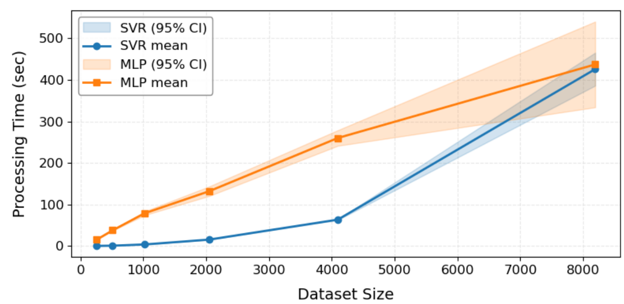

Fig. 4. **Comparison of Processing Times for SVR and MLP with confidence intervals**
***Source:* Compiled by the author**

A characteristic feature of both methods is the widening of confidence intervals when sample size exceeds 4096 points, indicating increased variability in processing time for large datasets.

Impact of Control Points on Prediction Quality
The study of control points' influence on prediction quality encompassed the comprehensive analysis of both their absolute quantity and relative proportion in the overall training sample.

With insufficient data volume, both advanced predictive methods demonstrate notably destructive values of the determination coefficient (R^2): for SVR, the minimum value reaches -3.971, and for MLP, it is approximately -1.318. Significantly increasing the training sample size substantially improves prediction quality across all metrics, which is convincingly confirmed by strong positive correlation coefficients (0.654 for SVR and 0.740 for MLP). The optimal number of control points for both sophisticated methods was determined to be 1638, providing maximum R^2 values of 0.808 for SVR and 0.796 for MLP. As clearly illustrated in Fig. 5, the overall prediction quality effectively stabilizes after reaching approximately 800 control points.

The detailed analysis of the relative number of control points' impact (Fig. 6) revealed several significant differences between the approaches when working with limited data quantities:

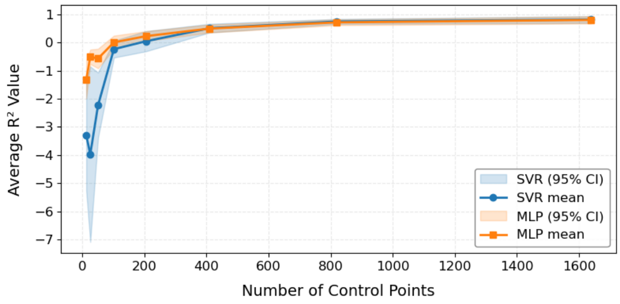

Fig. 5. **Comparison of Prediction Accuracy for SVR and MLP with Confidence Intervals**
Source: **compiled by the author**

– at 5 % control points: MLP maintains partial predictive ability (R^2=0.126±0.195), while SVR shows complete loss of prediction capability with negative results (R^2=-0.063±0.339);

– at 10 % points: MLP shows noticeable improvement in performance (R^2=0.246±0.159), while SVR continues to consistently yield negative prediction results (R^2=-0.133±0.320);

– using 20 % control points proved particularly optimal in this experimental context, where SVR demonstrates slightly better overall efficiency (R^2=0.547±0.124) compared to MLP (R^2=0.523±0.134).

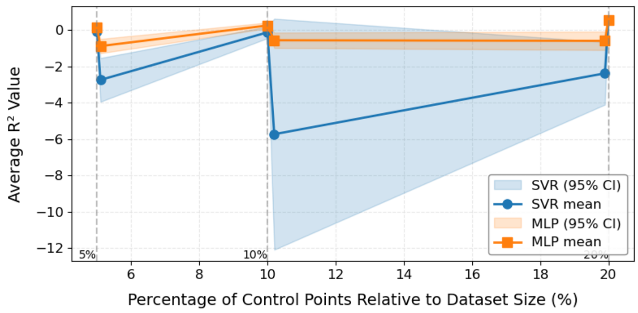

Fig. 6. **Comparison of Prediction Accuracy with confidence intervals, in Relation to the Percentage of Control Points**
Source: **Compiled by the author**

Thus, the MLP approach consistently demonstrates greater algorithmic stability with limited data availability, although both computational methods generally require sufficient training sample size to achieve acceptable prediction quality for practical applications

Analysis of Forecasting Methods Effectiveness The final comprehensive quantitative comparison of Support Vector Regression (SVR) and Multi-Layer Perceptron (MLP) methods was meticulously conducted on an optimized dataset consisting of 8192 training points and 1638 control points. The statistical significance of all observed differences between the methods was rigorously evaluated using Student's t-test with a conventional statistical significance level of 0.05.

When predicting Output X parameter (Fig. 7a), both advanced methods demonstrate remarkably robust noise resistance characteristics: the determination coefficient (R^2) decreases surprisingly insignificantly – from 0.99 to 0.966-0.967 even at maximum experimental noise level, indicating exceptionally robust performance under challenging conditions. The Root Mean Square Error (RMSE) shows a moderate but controlled increase from 0.050 to 0.105-0.106, however, the difference between both methods remains statistically insignificant (p=0.808), suggesting highly comparable prediction capabilities in real-world scenarios.

Predicting Output Y parameter proved to be consistently the most challenging aspect of the entire analytical process (Fig. 7b). Under maximum noise conditions, the determination coefficient experiences a substantial decrease to approximately 0.350 for SVR and 0.263 for MLP, while RMSE demonstrates a significant increase of more than twofold - from 0.012 to 0.026-0.027, clearly highlighting the inherent complexity of this particular prediction task within the experimental framework.

For Z1 Flow prediction parameter analysis (Fig. 7c), the initial prediction accuracy is notably high ($R^2 \approx 0.909$ for SVR, 0.901 for MLP), but experiences considerable performance degradation at maximum noise level, systematically decreasing to 0.685 and 0.648 respectively. The RMSE metric shows a substantial increase from 0.285 to 0.675-0.705, though the differences between methods remain statistically insignificant (p = 0.717), effectively maintaining their performance equivalence across the noise spectrum.

The detailed prediction of Z2 Flow parameter (Fig. 7d) is characteristically defined by consistently high accuracy under minimal noise conditions (R^2>0.917) and displays moderate gradual degradation at maximum noise levels (R^2≈0.721 and 0.702). The Root Mean Square Error demonstrates an approximate doubling in magnitude – from 0.265-0.267 to 0.549-0.568, while both computational methods maintain statistical equivalence in their overall performance metrics (p=0.433).

The comprehensive analysis of methods' noise resistance capabilities using the ΔRMSE indicator systematically revealed varying levels of model sensitivity when predicting different output parameters: ranging from 147 % for Z1 Flow to 114% for Z2 Flow across test conditions.

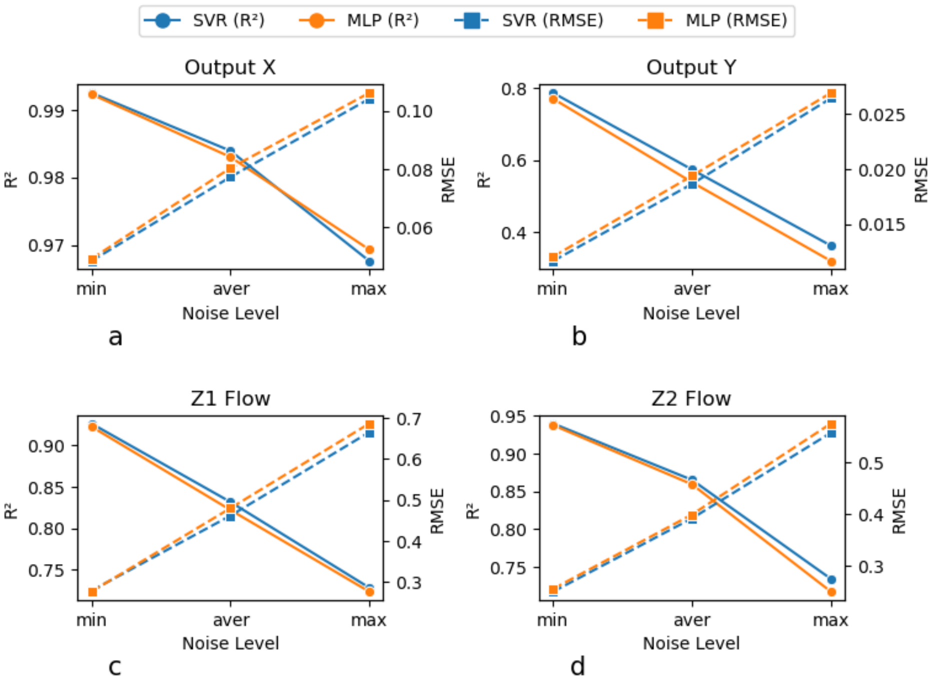

Fig. 7. **Comparison of SVR and MLP methods performance for different parameters prediction under various noise levels:**
a – Output X; b – Output Y; c – Z1 Flow; d – Z2 Flow
Source: **compiled by the author**

Both prediction methods consistently demonstrate statistically identical noise resistance characteristics throughout the experimental range, indicating fundamentally similar algorithmic response patterns to increasing levels of input data noise.

Summarizing the comprehensive research results and experimental findings, both computational methods demonstrate particularly impressive high noise resistance capabilities when accurately predicting Output X parameter, while showing highest sensitivity and vulnerability when predicting the more complex Output Y parameter. The SVR method consistently demonstrates slightly superior numerical results across most evaluated parameters, although this marginal advantage does not reach statistical significance threshold in any experimental case. It's importantly noteworthy that the practical SVR implementation requires notably longer processing time in all test scenarios, averaging 20-30 % more computational resources compared to the more efficient MLP approach. A significant additional observation from this study is that the number of statistical outliers in prediction quality metrics shows a natural and consistently expected increase with rising noise levels for both computational methods. These collective findings strongly reinforce the critical importance of utilizing sufficiently large comprehensive datasets and carefully maintaining an optimal number of control points to reliably achieve and consistently maintain acceptable prediction quality standards in diverse practical applications.

5. DISCUSSION OF OBTAINED RESULTS

Technical Characteristics: Input parameters obtained by cubic interpolation have a smoothed form, whereas output signals generated by the k-NN method only approximate such a form. To ensure consistency, it is advisable to apply k-NN to the interpolated input signals.

Noise Impact: Experiments have shown varying sensitivity of parameters to noise. The high stability of quality indicators is explained by the inertia of the process, while the higher sensitivity of flow parameters is due to equipment vibrations and pressure fluctuations.

Filtration Efficiency: The Kalman filter is suitable for parameters with slow dynamics, while wavelet filtration is appropriate for parameters with rapid changes. With limited computational resources, preference should be given to wavelet filtration due to its lower computational complexity.

Sample Size: The optimal size of the training sample is 8192 records, with 1638 (20 %) control points, providing a balance between training quality and generalization ability.

Computational Efficiency: SVR demonstrates 20-30% longer processing time compared to MLP.

As data volume increases, processing time for MLP grows linearly, while for SVR it grows non-linearly ($O(n^2)$). To optimize the computational process, it is proposed to use physical laws, particularly mass conservation principles.

Practical Recommendations: For parameters with high dynamics, it is recommended to increase measurement frequency and apply wavelet filtration. For more stable parameters, standard measurement frequency, Kalman filtering, and possible sample size reduction are sufficient. From a computational perspective, MLP is recommended for environments with limited resources, while SVR requires more computational power.

CONCLUSIONS

The research experimentally proves the effectiveness of combining filtration and regression methods for predicting noisy time series in industrial processes. The main results correspond to the assigned tasks and align with the goal of developing an integrated model.

A structural scheme of information technology has been developed, combining adaptive filtration and regression processes for effective time series prediction. An experimental database of noisy time series with various levels of normally distributed noise was created, which allowed establishing the optimal size of the training sample (8192 records) and the number of control points (1638).

A filtration quality assessment system is proposed through a comprehensive OFS indicator that integrates smoothing efficiency, noise reduction, and signal characteristic preservation. The system provides adaptability through automatic selection of the optimal filtration method depending on input signal characteristics, which meets the task of implementing and optimizing filtration algorithms.

Quantitative characteristics of noise impact on the predictive capability of regression models (SVR and MLP) have been established. SVR provides higher prediction accuracy at low noise levels, while MLP demonstrates greater stability at high noise levels. Computational efficiency analysis of the methods confirms a linear dependence of processing time on data volume for MLP and nonlinear growth for SVR.

The proposed approach provides a 15-20% increase in prediction accuracy compared to machine learning methods without preliminary filtration. The practical value of the results lies in their applicability to industrial process control systems where data noise problems exist. The developed method can be applied not only to the studied system but also to other similar technological processes. A promising direction for optimizing learning models through the use of physical process patterns has been identified, which allows improving the metrological characteristics of prediction.

FUTURE WORK

Future research stems from an analysis of limitations identified experimentally. They encompass technical improvements, parameter optimization, analysis of noise impact, and enhancement of data preprocessing.

From a technical perspective, it is necessary to develop adaptive filtering methods for various parameters and investigate hybrid forecasting methods. It is important to study the influence of process non-stationarity on forecasting quality.

Parameter optimization should focus on automatic methods to reduce manual configuration, including optimization of SVR kernel parameters and MLP architecture.

Research on noise with different distribution laws will expand understanding of system behavior. Studying noise effects characteristic of real measurement conditions will allow the development of methods adapted to various technological parameters.

Improvement of data preprocessing should focus on reducing data volume without compromising forecasting quality and utilizing additional information from adjacent systems.

REFERENCES

1. Yuan, X., Li, J. & Kuruoglu, E. E. “Robustness enhancement in neural networks with alpha-stable training noise”. *Digital Signal Processing*. 2025; 156: 104778, https://www.scopus.com/record/display.uri?eid=2-s2.0-85204880798&origin=resultslist. DOI: https://doi.org/10.1016/J.DSP.2024.104778.

2. Benedetti, M., Ventura, E., Benedetti, M. & Ventura, E. “Training neural networks with structured noise improves classification and generalization”. *Journal of Physics A: Mathematical and Theoretical*. 2024; 57(41): 415001, https://www.scopus.com/record/display.uri?eid=2-s2.0-85205390279&origin=resultslist. DOI: https://doi.org/10.1088/1751-8121/AD7B8F.

3. Metzner, C., Schilling, A., Maier, A. & Krauss, P. “Recurrence resonance – noise-enhanced dynamics in recurrent neural networks”. *Frontiers in Complex Systems*. 2024; 2. DOI: https://doi.org/10.3389/fcpxs.2024.1479417.

4. Ibias, A., Capaa La, K., Varma, V. R., Drozd, A. & Sousa, J. “Improving Noise Robustness through Abstrations and its Impact on Machine Learning”. 2024. DOI: https://doi.org/10.48550/arXiv.2406.08428.

5. Ganie, A. G. & Dadvadipour, S. “Exploring noise-induced techniques to strengthen deep learning model resilience”. *Pollack Periodical*. 2024; 19 (3): 8–13, https://www.scopus.com/record/display.uri?eid=2-s2.0-85198914317&origin=resultslist. DOI: https://doi.org/10.1556/606.2024.01068.

6. Awad, M. & Khanna, R. “Support vector regression”. In: *Efficient Learning Machines*. 2015. p. 67–80. DOI: https://doi.org/10.1007/978-1-4302-5990-9_4.

7. Zhang, G., Patuwo, B. E. & Hu, M. Y. “Forecasting with artificial neural networks: The state of the art”. *International Journal of Forecasting*. 1998; 14 (1): 35–62. DOI: https://doi.org/10.1016/S0169-2070(97)00044-7.

8. Akhlaghi, S., Zhou, N. & Huang, Z. “Adaptive adjustment of noise covariance in Kalman filter for dynamic state estimation”. *IEEE Power and Energy Society General Meeting*. 2018. p. 1–5, https://www.scopus.com/record/display.uri?eid=2-s2.0-85046375269&origin=resultslist. DOI: https://doi.org/10.1109/PESGM.2017.8273755.

9. Mallat, S. “A Wavelet Tour of Signal Processing: The Sparse Way”. 2008, https://www.scopus.com/record/display.uri?eid=2-s2.0-85134554666&origin=resultslist., DOI: https://doi.org/10.1016/B978-0-12-374370-1.X0001-8.

10. Peterson, L. “K-nearest neighbor”. *Scholarpedia*. 2009; 4 (2): 1883. DOI: https://doi.org/10.4249/SCHOLARPEDIA.1883.

11. Box, G. E. P., Jenkins, G. M., Reinsel, G. C. & Ljung, G. M. “Time Series Analysis: Forecasting and Control”. *5th Edition. Hoboken: USA; Wiley Publishing Ltd*. 2016. DOI: https://doi.org/10.1111/jtsa.12194.

12. Lim, B. & Zohren, S. “Time-series forecasting with deep learning: a survey”. *Philosophical Transactions of the Royal Society A*. 2021; 379 (2194), https://www.scopus.com/record/display.uri?eid=2-s2.0-85101380645&origin=resultslist, DOI: https://doi.org/10.1098/RSTA.2020.0209.

13. Wang, J., Yang, W., Du, P. & Niu, T. “A novel hybrid forecasting system of wind speed based on a newly developed multi-objective sine cosine algorithm”. *Energy Conversion and Management*. 2018; 163: 134–150, https://www.scopus.com/record/display.uri?eid=2-s2.0-85042285736&origin=resultslist. DOI: https://doi.org/10.1016/J.ENCONMAN.2018.02.012.

14. Bergstra, J., Ca, J. B. & Ca, Y. B. “Random Search for Hyper-Parameter Optimization Yoshua Bengio”. *Journal of Machine Learning Research*. 2012; 13: 281–305, https://www.scopus.com/record/display.uri?eid=2-s2.0-84857855190&origin=resultslist. – Available from: http://scikit-learn.sourceforge.net. – [Accessed: Jan, 2024].

15. Smola, A. J. & Schölkopf, B. “A tutorial on support vector regression”. *Statistics and Computing*. 2004; 14 (3): 199–222, https://www.scopus.com/record/display.uri?eid=2-s2.0-4043137356&origin=resultslist. DOI: https://doi.org/10.1023/B:STCO.0000035301.49549.88.

16. Navarrete, R. & Viswanath, D. “Support Vector Regression, Smooth Splines, and Time Series Prediction”. arXiv. DOI: https://doi.org/10.48550/arXiv.1511.00158.

17. Chen, P. & Lu, Y. Z. “Extremal optimization for optimizing kernel function and its parameters in support vector regression”. *Journal of Zhejiang University: Science C*. 2011; 12 (4): 297-306, https://www.scopus.com/record/display.uri?eid=2-s2.0-79955920897&origin=resultslist. DOI: https://doi.org/10.1631/JZUS.C1000110.

18. Sabzekar, M. & Hasheminejad, S. M. H. “Robust regression using support vector regressions”. *Chaos, Solitons & Fractals*. 2021; 144: 110738. DOI: https://doi.org/10.1016/J.CHAOS.2021.110738.

19. Pu, Y., Zhu, J. & Yan, T. “A Novel Hybrid Forecasting Model Based on Time Series”. *Communications in Computer and Information Science*. 2020; 1303: 469–482. DOI: https://doi.org/10.1007/978-981-33-6378-6_35.

20. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I. & Salakhutdinov, R. “Dropout: A Simple Way to Prevent Neural Networks from Overfitting”. *Journal of Machine Learning Research*. 2014; 15 (56): 1929–1958. – Available from: http://jmlr.org/papers/v15/srivastava14a.html. – [Accessed: Jan, 2024].

21. Oukhouya, H. & El Himdi, K. “Comparing Machine Learning Methods—SVR, XGBoost, LSTM, and MLP – For Forecasting the Moroccan Stock Market”. *Computer Sciences & Mathematics Forum*. 2023; 7 (1): 39. DOI: https://doi.org/10.3390/IOCMA2023-14409.

22. Samsudin, R., Shabri, A. & Saad, P. “A Comparison of Time Series Forecasting using Support Vector Machine and Artificial Neural Network Model”. *Journal of Applied Sciences*. 2010; 10 (11): 950–958. DOI: https://doi.org/10.3923/JAS.2010.950.958.

23. Paterakis, N. G., Mocanu, E., Gibescu, M., Stappers, B. & Van Alst, W. “Deep learning versus traditional machine learning methods for aggregated energy demand prediction”. *IEEE PES Innovative Smart Grid Technologies Conference Europe.* 2017. p. 1–6. DOI: https://doi.org/10.1109/ISGTEUROPE.2017.8260289.

24. Shen, X., Gong, X., Cai, Y., Guo, Y., Tu, J., Li, H., Zhang, T., Wang, J., Xue, F. & Lu, G. “Normalization and integration of large-scale metabolomics data using support vector regression”. *Metabolomics*. 2016; 12 (5). DOI: https://doi.org/10.1007/S11306-016-1026-5.

25. Ahsan, M. M., Mahmud, M. A. P., Saha, P. K., Gupta, K. D. & Siddique, Z. “Effect of Data Scaling Methods on Machine Learning Algorithms and Model Performance”. *Technologies.* 2021; 9 (3): 52, https://www.scopus.com/record/display.uri?eid=2-s2.0-85114463760&origin=resultslist. DOI: https://doi.org/10.3390/TECHNOLOGIES9030052.

26. Hui, Y., Wenzhu, S., Xiuzhi, Z., Guotao, Z. & Wenting, H. “Heuristic sample reduction based support vector regression method”. *IEEE International Conference on Mechatronics and Automation*. 2016: 2065–2069, https://www.scopus.com/record/display.uri?eid=2-s2.0-84991232622&origin=resultslist. DOI: https://doi.org/10.1109/ICMA.2016.7558884.

27. Mizutani, E. & Dreyfus, S. E. “On complexity analysis of supervised MLP-learning for algorithmic comparisons”. *Proceedings of the International Joint Conference on Neural Networks*. 2001; 1: 347–352, https://www.scopus.com/record/display.uri?eid=2-s2.0-0034856538&origin=resultslist. DOI: https://doi.org/10.1109/IJCNN.2001.939044.

28. Kalman, R. E. “A new approach to linear filtering and prediction problems”. *Journal of Fluids Engineering.* 1960; 82 (1): 35–45, https://www.scopus.com/record/display.uri?eid=2-s2.0-85024429815&origin=resultslist. DOI: https://doi.org/10.1115/1.3662552.

29. Simon, D. “Optimal State Estimation: Kalman, H infinity, and Nonlinear Approaches”. Hoboken: USA. 2006.

30. Mehra, R. K. “Approaches to Adaptive Filtering”. *IEEE Transactions on Automatic Control*. 1972; 17 (5): 693–698, https://www.scopus.com/record/display.uri?eid=2-s2.0-0015416561&origin=resultslist. DOI: https://doi.org/10.1109/TAC.1972.1100100.

31. Brown, R. G. & Hwang, P. Y. C. “Introduction to Random Signals and Applied Kalman Filtering: With MATLAB Exercises and Solutions”. 3rd ed. New York: USA. 1997.

32. Addison, P. S. “The illustrated wavelet transform handbook: introductory theory and applications in science, engineering medicine and finance”. CRC *Press.* 2020, https://www.scopus.com/record/display.uri?eid=2-s2.0-85140146116&origin=resultslist. – Available from: https://www.routledge.com/The-Illustrated-Wavelet-Transform-Handbook-Introductory-Theory-and-Applications-in-Science-Engineering-Medicine-and-Finance-Second-Edition/Addison/p/book/9780367574000. – [Accessed: Jan, 2024].

33. Donoho, D. L. & Johnstone, J. M. “Ideal spatial adaptation by wavelet shrinkage”. Biometrika. 1994; 81 (3): 425–455, https://www.scopus.com/record/display.uri?eid=2-s2.0-0041958932&origin=resultslist. DOI: https://doi.org/10.1093/BIOMET/81.3.425.

34. Tsai, V. C. “Understanding the amplitudes of noise correlation measurements”. *Journal of Geophysical Research: Solid Earth.* 2011; 116 (B9): 9311, https://www.scopus.com/record/display.uri?eid=2-s2.0-80053324653&origin=resultslist. DOI: https://doi.org/10.1029/2011JB008483.

35. Montgomery, D. C. “Design and Analysis of Experiments”. *Mycological Research*. 2017; 106 (11): 1323–1330. – Available from: https://www.researchgate.net/publication/362079778_Design_and_Analysis_of_Experiments_9th_Edition. – [Accessed: Jan, 2024].

36. Arts, L. P. A. & van den Broek, E. L. “The fast continuous wavelet transformation (fCWT) for real-time, high-quality, noise-resistant time–frequency analysis”. *Nature Computational Science*. 2022; 2 (1): 47–58. DOI: https://doi.org/10.1038/s43588-021-00183-z.

 ISSN 2663-0176 (Print)
ISSN 2663-7731 (Online)

37. Kavitha, R. & Kumar, P. C. M. "A Comparison between MLP and SVR Models in Prediction of Thermal Properties of Nano Fluids". *Journal of Applied Fluid Mechanics*. 2018; 11: 7–14. DOI: https://doi.org/10.36884/jafm.11.SI.29411

Conflicts of Interest: The authors declare that they have no conflict of interest regarding this study, including financial, personal, authorship or other, which could influence the research and its results presented in this article

Received 14.01.2025
Received after revision 13.03.2025
Accepted 20.03.2025

DOI: https://doi.org/10.15276/hait.08.2025.1
УДК 004.832.2:622.7

Методи фільтрації та регресії для прогнозування зашумлених часових рядів на основі машинного навчання

Воловецький Олександр Остапович
ORCID: https://orcid.org/0009-0003-1703-387X; ovolovetskyi@gmail.com. Scopus Author ID: 59366887600
Криворізький національний університет, вул. Віталія Матусевича, 11. Кривий Ріг, 50027,Україна

АНОТАЦІЯ

Прогнозування параметрів у промислових процесах значно ускладнюється наявністю шуму в послідовних вимірюваннях, що зменшує ефективність контролю технологічного процесу. Метою дослідження є розробка інтегрованої моделі, яка поєднує методи адаптивної фільтрації шуму та регресію для покращення точності прогнозування зашумлених часових рядів із використанням алгоритмів машинного навчання. Під час дослідження була створена комплексна база даних часових рядів із різними рівнями та типами шуму, що забезпечило ретельну перевірку ефективності запропонованих методів. Набори даних були розроблені з урахуванням специфіки технологічних процесів та різноманітності шумових патернів, що дозволило точно оцінити розроблені методи в різних умовах. У рамках розробки методів адаптивної фільтрації шуму були впроваджені та оптимізовані фільтр Калмана та вейвлет-фільтрація. Встановлено зв'язок між ефективністю методів фільтрації та часовими патернами: для параметрів, що швидко змінюються, вейвлет-фільтрація забезпечує вищу ефективність згладжування, тоді як фільтр Калмана краще зберігає характеристики сигналу для більш стабільних послідовностей. Для вирішення задачі прогнозування часових рядів були впроваджені та протестовані два алгоритми регресії – регресія опорних векторів та багатошаровий перцептрон. Було доведено, що регресія опорних векторів демонструє кращі результати з даними з низьким рівнем шуму, тоді як багатошаровий перцептрон показує вищу стабільність в умовах значного шуму, особливо після попередньої фільтрації. Для оцінки ефективності запропонованих рішень була розроблена комплексна система оцінки якості, яка одночасно враховує ефективність прогнозування, часові аспекти, характеристики шуму та обчислювальну складність. Експериментальне підтвердження демонструє, що розроблений підхід покращує точність прогнозування порівняно з методами машинного навчання без попередньої фільтрації, зберігаючи прийнятну обчислювальну складність. Розроблений підхід є перспективним для промислових застосувань, включаючи моделювання процесів збагачення залізної руди, де шумостійке прогнозування важливе для контролю процесу. Запропоновані методи можуть бути поширені на різні промислові процеси з подібними часовими даними та характеристиками шуму, особливо в металургійній, хімічній та харчовій промисловості

Ключові слова: Фільтр Калмана; вейвлет-фільтрація; регресія опорних векторів; багатошаровий перцептрон; шумостійке прогнозування

ABOUT THE AUTHOR

Oleksandr O. Volovetskyi - Postgraduate, Department of Automation, Computer Science and Technologies/ Kryvyi Rih National University, 11 Vitaliy Matusevych St. Kryvyi Rih, 50027, Ukraine
ORCID: https://orcid.org/0009-0003-1703-387X; ovolovetskyi@gmail.com. Scopus Author ID: 59366887600
Research field: Industrial automation, machine learning, time series analysis, intelligent control systems.

Воловецький Олександр Остапович - аспірант кафедри Автоматизації комп'ютерних наук та технологій. Криворізький національний університет, вул. Віталія Матусевича, 11. Кривий Ріг, 50027, Україна